# (ICW) The YouTube Algorithm and Manufacturing Consent

***2024-11-17***

*By NRU*

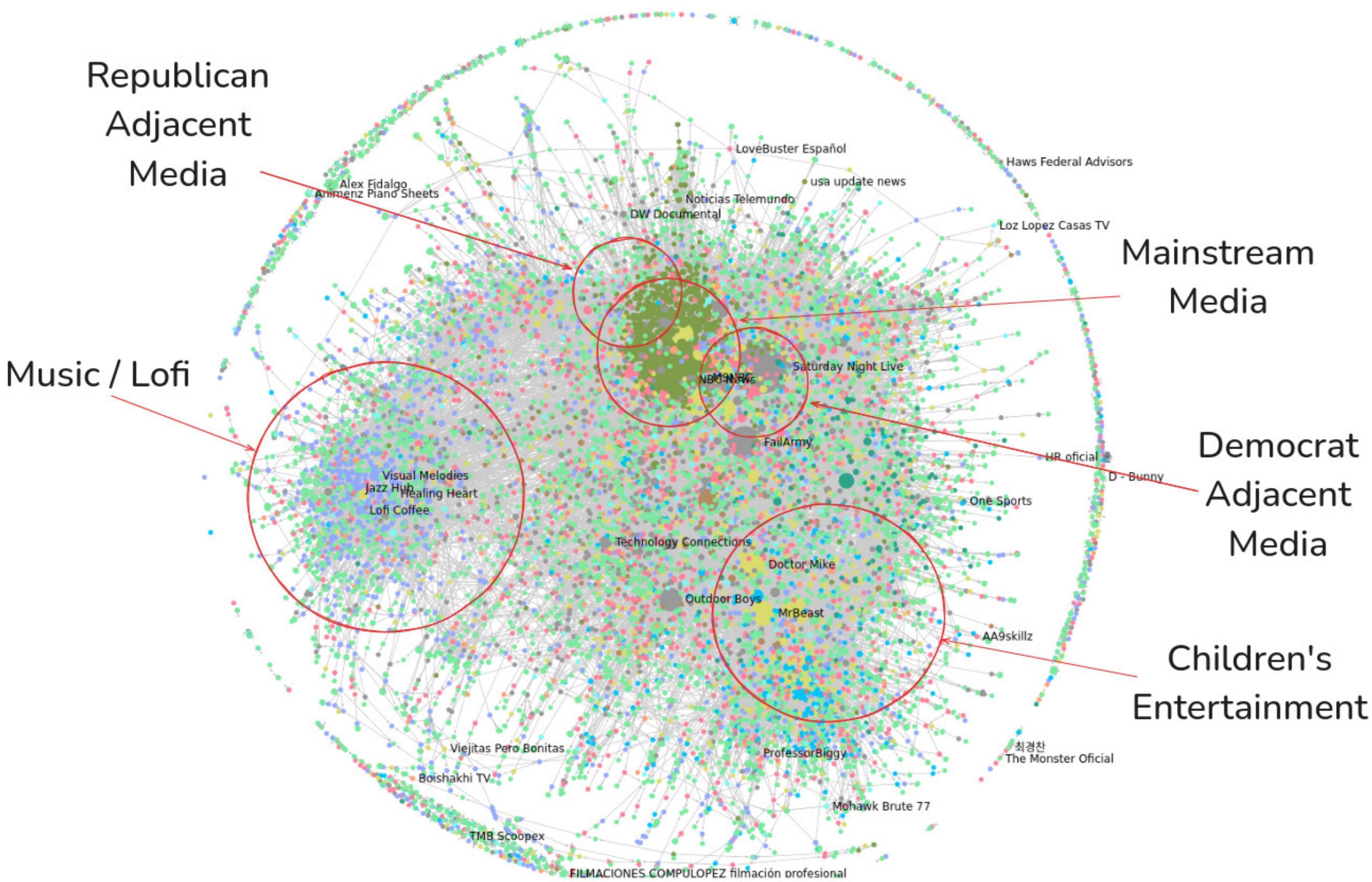


*Figure 0. The YouTube Recommendation Network.*

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# Overview

In order to study the the YouTube algorithm and how it influences the information its 3 billion users consume, I created a bot to watch over 23,000+ YouTube videos and collect over 520,000 video recommendations. To obtain the data, 1000 different bots randomly click and watch videos that are recommended to them. Below is a list of key observations made during the study:

**YouTube actively promotes large corporate media over smaller independent media.**

- 84% of the top recommended videos were from large corporate YouTube channels
- In the news feed, 96% of all news recommended were from main stream media news

**No matter whether a user is new to the platform or an existing user with an established watch history, the user is almost always one video away from being sucked in to the "far right rabbit hole".**

- We present evidence of several bots stumbling inside far right rabbit holes just from randomly clicking on recommended videos

**YouTube heavily promotes content related to "culture wars", promoting right wing influencers while ignoring left wing independent influencers.**

- Right wing influencers were recommended 322 times, while left wing media influencers were recommended 1 time.

**Given the choice to uphold YouTube's own community guidelines or selectively ignore them to make money, YouTube will likely choose the latter when the incentives are significant enough. This is evident in YouTube's role in promoting streamers who participate in:**

- Culture wars, Gambling streams aimed at children (29% of all gaming streams were related to gambling), normalization of racist and sexist views.

I also discuss the role of billionaire funding being the a key driver in the growing influence of right wing media on online platforms like YouTube. Views that were considered fringe in the past, have became normalized. This is exemplified by the fact that 9 of the 10 most viewed streams during the 2024 American elections were from right-wing creators; of which, 7 built their initial audiences on YouTube.

While not the first study of its kind, this study is probably the largest public study of the YouTube algorithm as of 2024. All data is available for download in the “data availability” section.

# Intro – Did YouTube change or have we just gotten older?

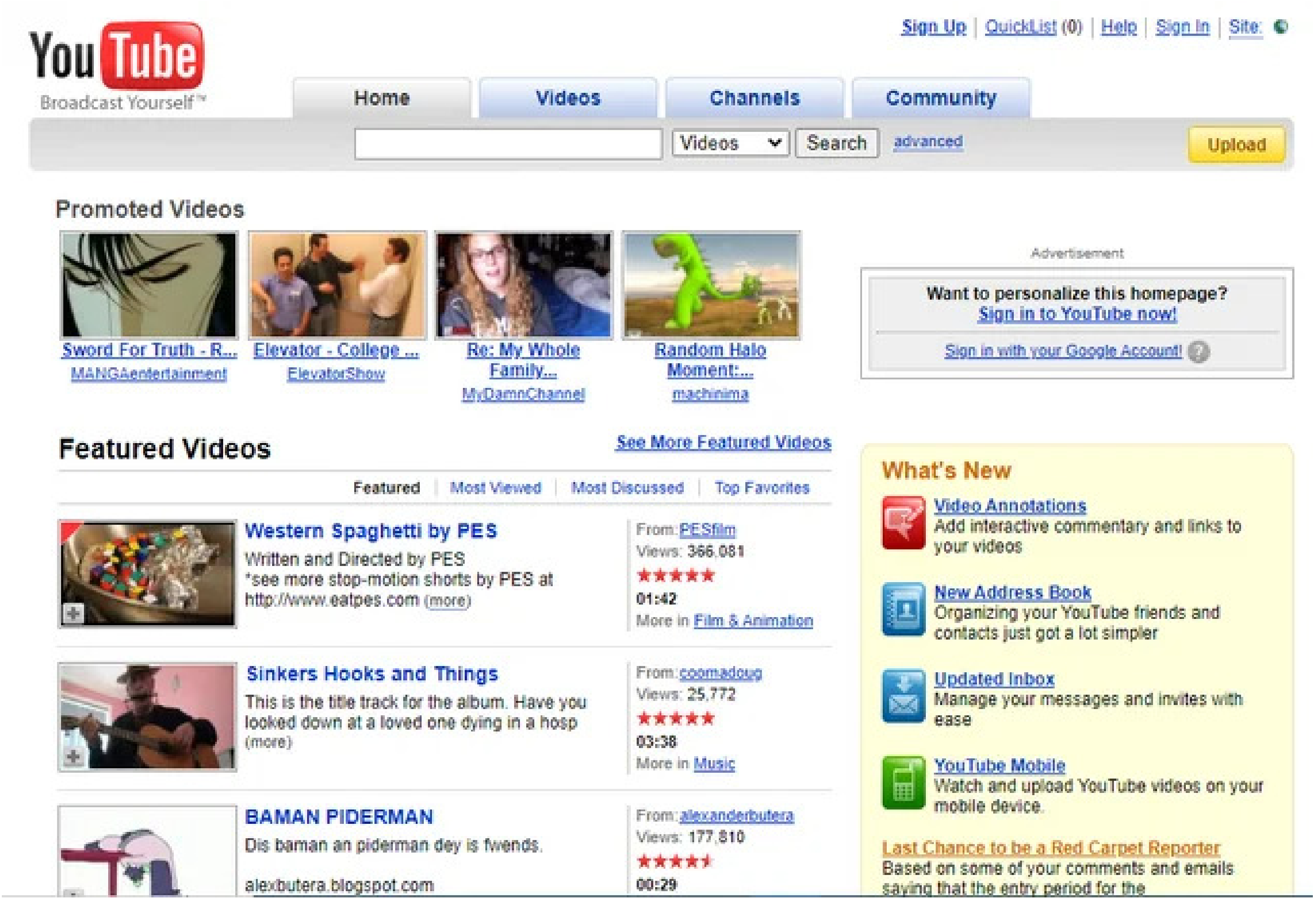



*Figure 1. YouTube homepage, 2008.*

One of the most common opinions I have heard in the last couple of years is that YouTube is no longer what it used to be. Many YouTube users I've heard from both online and in real life complain that the YouTube "algorithm" has made a shift from promoting your everyday content creator to promoting:

- **Large corporate media**, such as Saturday Night Live and Jimmy Kimmel Live
- **Polarizing mainstream media news** such as Sky News Australia and Forbes Breaking News
- **Right wing political influencers** such as Charlie Kirk and Tim Pool
- **Large YouTube Productions** such as Mr. Beast or Dhar Mann

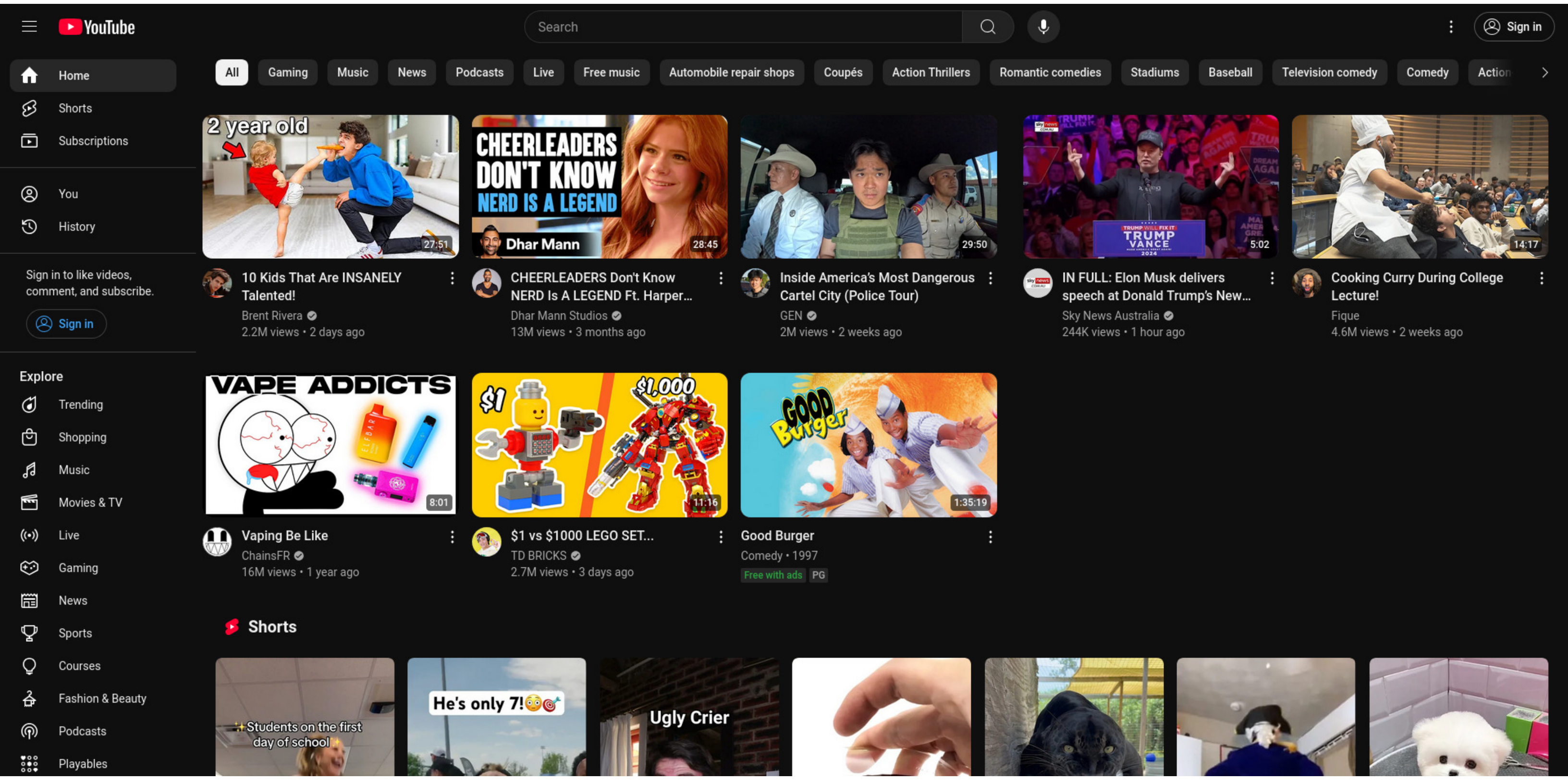


*Figure 2. YouTube homepage, 2024.*

Are these opinions based on nostalgia for [videos]() they've watched in their childhood, or are they based on natural reactions to the constantly evolving recommendation system?

To find out whether these claims anecdotal, I would need to access YouTube's internal database of historical recommendations. However even if I did, YouTube doesn't store user recommendation data indefinitely, making it difficult to remove the influence of the user's full history from their current recommendations.

Instead I will create an army of bots to scrape, a smaller representative sample of data.

The purpose of this investigation is to answer the following questions.

1. Is YouTube promoting certain kinds of creators over others?
2. How easy is it for a YouTube user to get introduced to divisive and radicalizing content?
3. Is YouTube a hyper-corporate entity where money must be made at the cost of their integrity?

# Recommendation Systems – An AI powered feedback loop that grows more powerful with user data

Before I show the results, I would like to share a high level overview of how the YouTube "algorithm" actually works.

Almost all large multi-billion dollar corporations that do any form of media related recommendations for 100M+ users will likely have a similar setup to the one I'm about to share.

Below is a step by step explanation of how a video is delivered all the way from YouTube's video library to your screen.

1. Using user information collected by Google and 3rd parties, **filter the initial library of 10M+ videos to the 1000 most relevant videos**. This is usually done using a combination of filtering rules that are explicitly specified by YouTube (e.g. favor advertiser friendly creators, retrieve content in users language). A small and fast neural network can be used to aid in this process.
2. Using user information collected by Google and 3rd parties, **filter the 1000 videos from the previous step, find and rank the 20 most relevant videos.** This is usually done using a large but slow neural network machine learning model.
3. When the user watches a video, provide them with the top 20 video recommendations in their video feed.
4. Track the users inputs. The two main ones are **whether the user clicks on a video, and/or watches it for more than 30 seconds**
5. Using user information collected by Google and 3rd parties and the user's watch history, recommend the next set of videos.

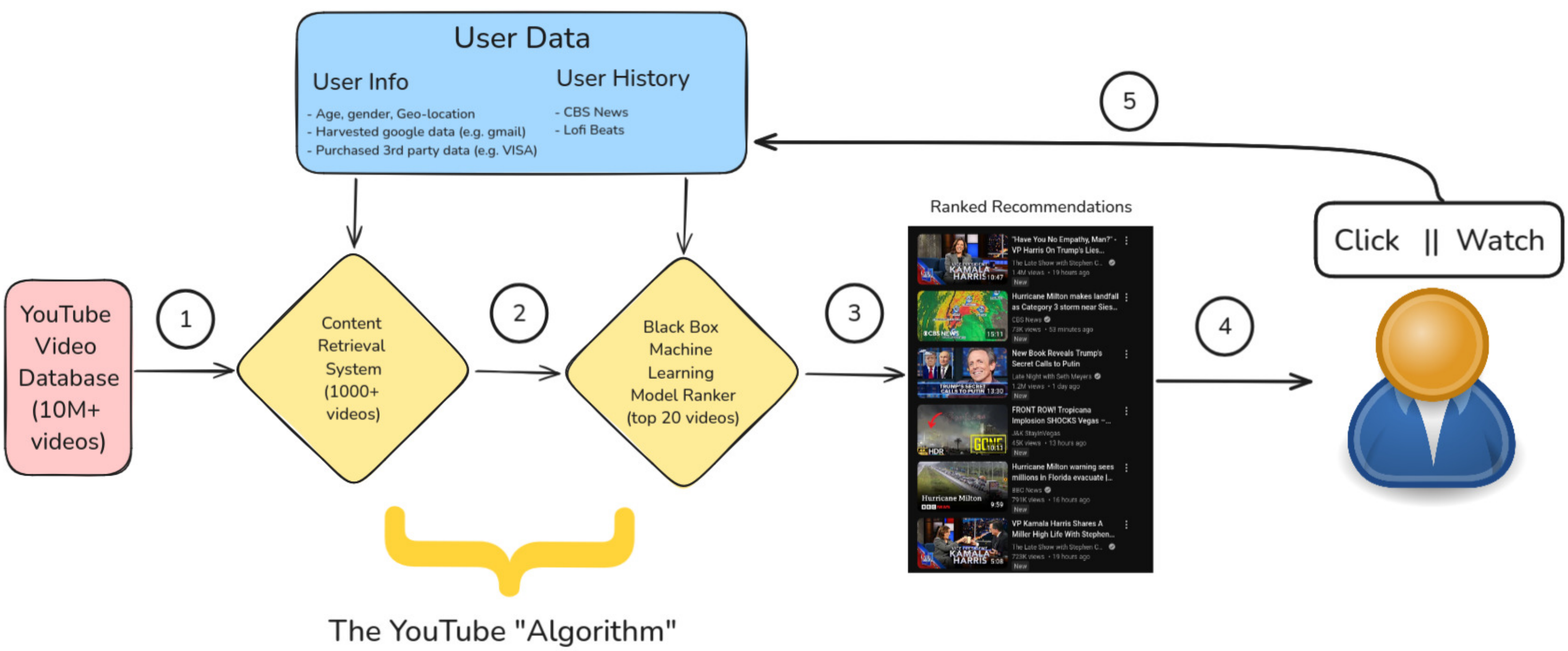



*Figure 3. Simplified version of YouTube's recommendation system, aka, the YouTube algorithm.*

The YouTube algorithm's job is to select and rank the top 20 most relevant videos and recommend them to you, so that you click the video (objective 1) and watch it for at least 30 seconds (objective 2). In doing so, YouTube keeps the user **spending more time on its platform, in turn watching more ads, which makes them money**.

Data from 2023 shows that 77.8% of Google’s revenue comes from advertising revenue.

> *Authors note: The above is a generalization of Google’s tech stack, these are not actual figures used.*

# Recommendation Systems – There is more than one "YouTube Algorithm".

I also want to highlight that YouTube likely does not use a large singular model for their entire website. **Each different type of feed is likely powered by a different model**. So for example, the YouTube home page, video recommendation feed, and shorts page, all likely use different models in the backend.

This has several implications on the experiment, which I will discuss in the methods section.


*Figure 4. Simplified version of YouTube's model stack. There is a separate model for each type of recommendation feed.*

# Results – The YouTube Algorithm Visualized

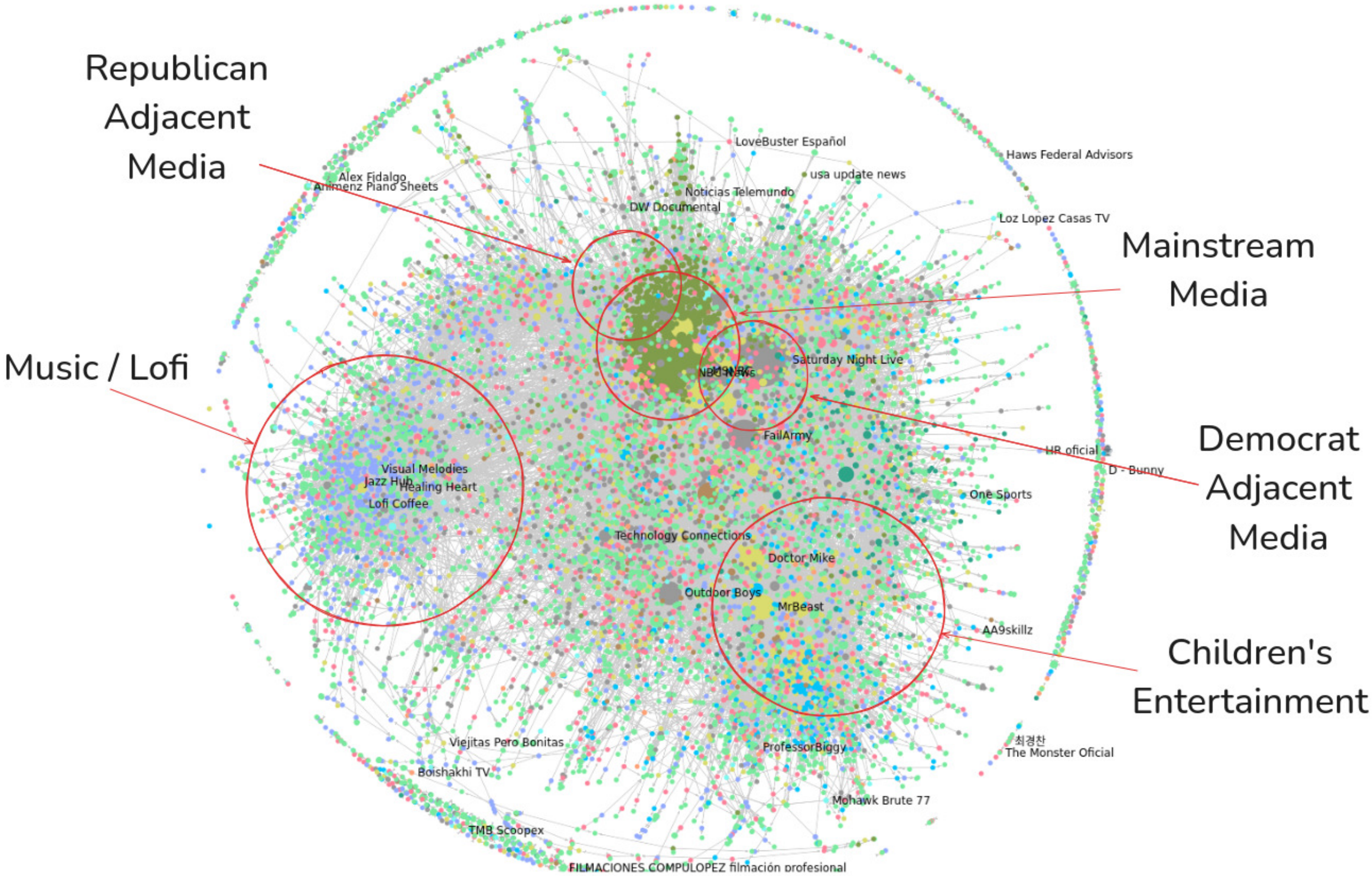



*Figure 5. The YouTube Recommendation Network.*

The figure above is a graph based illustration of the YouTube recommendation network. It is composed of 529,000+ video recommendations obtained from watching 23,400+ videos using 1000 bots.

I **highly recommend downloading the interactive version** of this recommendation network and exploring it on your own, as most of the analysis in this investigation covers only a small section of it.

The recommendation network is obtained using a bot that does the following procedure:

1. Watch a video for a random amount of time (watch amount will be >30 seconds)
2. Using the list of recommended videos from the right-hand feed, randomly select a video to visit (various selection strategies using statistical distributions and LLMs are explored)
3. Go back to step 1

A more detailed explanation of the methodology will be covered in the methods section. The recommendation network is available for  download in the "data availability" section at the bottom of the article. I also include the raw data from this experiment, as well as a similar experiment I ran inside the United Kingdom.

# Results – Does YouTube recommend certain channels more than others?

Yes. The **overwhelming majority** of recommendations given by YouTube were of either large **mainstream media or large corporate YouTube channels**. The table below contains the top 50 recommended YouTube channels from the 529,000+ video recommendations. Of the top 50, only 8 (16%) of YouTube channels can be considered non-mainstream-media non-corporate YouTube channels.

*Figure 6. Top 50 recommended YouTube video channels*

| Video Author | Number of Recommendations |
|---|---|
| NBC News | 8249 |
| FOX Weather | 5757 |
| MSNBC | 5427 |
| Saturday Night Live | 5259 |
| CBS News | 5196 |
| Technology Connections | 4602 |
| CNN | 4473 |
| Jonathan Petramala | 4201 |
| Markiplier | 4169 |
| Deji | 3911 |
| WINK News | 3478 |
| The Rich Eisen Show | 3405 |
| Inside Edition | 3351 |
| Nintendo of America | 3199 |
| ABC News | 3082 |
| FOX 4 Now | 3005 |
| ABC Action News | 2943 |
| Fortnite | 2892 |
| MrBeast | 2863 |
| WFLA News Channel 8 | 2804 |
| JENNIE | 2803 |
| FailArmy | 2785 |
| Jimmy Kimmel Live | 2550 |
| The Late Show with Stephen Colbert | 2461 |
| Sky News Australia | 2411 |
| Outdoor Boys | 2383 |
| FOX 11 Los Angeles | 2330 |
| FOX 4 Dallas-Fort Worth | 2185 |

| **Video Author** | **Number of Recommendations** |
|---|---|
| Late Night with Seth Meyers | 2117 |
| WFAA | 2062 |
| Kitchen Nightmares | 1908 |
| WPLG Local 10 | 1900 |
| Doctor Mike | 1891 |
| 10 Tampa Bay | 1868 |
| FOX 9 Minneapolis-St. Paul | 1840 |
| Forbes Breaking News | 1796 |
| Throttle House | 1763 |
| LiveNOW from FOX | 1641 |
| Dhar Mann Studios | 1599 |
| NFL | 1595 |
| CBS Miami | 1538 |
| Jana Duggar | 1397 |
| 60 Minutes | 1352 |
| Livestream Events | 1333 |
| CBS New York | 1318 |
| 9NEWS | 1295 |
| Dear Gamer | 1279 |
| Ryan Hall, Y'all | 1277 |
| LLOUD Official | 1208 |
| The Bergamot | 1173 |

*Authors note: I am aware the the definition of "mainstream media" or "large corporate YouTuber" is somewhat subjective and can vary from one person to another. My personal definition are entities that do originate from main stream media sources (e.g. TV) or are multimillion dollar YouTube megastars with at least a dozen employees.*

# Results – Which YouTube channels are people engaging with?

A good proxy of channel engagement is whether someone repeatedly watches a YouTube channel. If we make the assumption that the YouTube algorithm is a good model for user behavior, then we can use the recommendations as user behavior signals.

For a given video, if we take the number of recommendations that are from the same channel, and divide that by the total number of recommendations (regardless of source) we can get the self recommendation rate.

$$\text{SelfRecommendationRate} = \frac{R_s}{R_s + R_o}$$

$R_s$ : Number of recommendations from same video author
$R_o$ : Number of recommendations from other video authors

If a channel has a high self recommendation rate (closer to 1), it means the users are watching their videos repeatedly, rather than just once. Conversely, a low self recommendation rate (closer to 0) means that users are not watching other videos from the author. As soon as they see one video they no longer watch the channel again. This often happens with viral videos.

*Figure 7. Top 50 recommended YouTube video channels*

| Video Author | Self Recommendation Rate (%) |
|---|---|
| Technology Connections | 50.3% |
| Doctor Mike | 43.3% |
| Markiplier | 43.1% |
| Kitchen Nightmares | 40.5% |
| Outdoor Boys | 38.4% |
| Will Tennyson | 31.4% |
| Dhar Mann Studios | 30.5% |
| MSNBC | 28.3% |
| A&E | 26.9% |
| NFL | 25.7% |
| FailArmy | 25.0% |
| Saturday Night Live | 24.1% |
| Relax Jazz Cafe | 23.8% |
| Brian Tyler Cohen | 23.6% |

| Video Author | Self Recommendation Rate (%) |
|---|---|
| Jimmy Kimmel Live | 21.9% |
| Sky News Australia | 21.9% |
| Inside Edition | 21.4% |
| Daily Dose Of Internet | 20.6% |
| The Late Show with Stephen Colbert | 19.6% |
| MrBeast | 18.5% |
| Fighting Spirit | 18.5% |
| Forbes Breaking News | 17.9% |
| NBC News | 17.3% |
| Late Night with Seth Meyers | 17.2% |
| CNN | 15.4% |
| Heavi | 15.1% |
| ABC Action News | 10.7% |
| Artesanato e Decoração | 10.3% |
| CBS News | 9.7% |
| StormChasingVideo | 8.8% |
| ABC News | 8.7% |
| FOX Weather | 8.2% |
| 10 Tampa Bay | 8.1% |
| Jonathan Petramala | 7.3% |
| FOX 4 Now | 7.2% |
| KTLA 5 | 4.7% |
| WPLG Local 10 | 4.5% |
| CBS Miami | 3.2% |
| FOX 4 Dallas-Fort Worth | 2.7% |
| FOX 11 Los Angeles | 2.1% |
| 9NEWS | 1.1% |
| The Bergamot | 0.2% |

For those unfamiliar with these channels, let me explain the results.

At the top of the list (rate >30%), are the video channels with the highest self recommendation rates. With the exception of the TV show “Kitchen Nightmares” and “Dhar Mann Studios”, the vast majority of channels here are made by YouTubers with loyal fanbases.

In the middle of the list (>10% & <30%), are the video channels with intermediate self recommendation rates. These seem to be established large YouTube brands (MrBeast, Daily Dose Of Internet), TV shows (Saturday Night Live, The Late Show with Stephen Colbert), and news (NBC News, CNN)

At the bottom of the list (<10%) are the video channels with the lowest self recommendation rates. The vast majority look like local news or weather related channels. YouTube channels like Jonathan Petramala and The Bergamot both made viral videos during the time of this experiment (2024-10-09) covering Hurricane Helene.

The conclusion here is that channel engagement on YouTube is typically highest when viewers are shown popular independent YouTube creators, followed by mainstream TV shows and then local news, in that order.

> *Authors note: In my personal opinion, the results turned out better than I expected. The ranking of video authors from the self recommendation ratio seems inline with my expectations of what the YouTube community generally like to watch. I would also not be surprised if this number correlated quite nicely with advertiser CPM. The results also provide a good validation signal for the assumption I made earlier that the YouTube algorithm is a good model for user behavior.*

# Result – How many clicks is the average YouTube user away from falling into a far-right rabbit hole?

In the worst case scenario, a YouTube user is **one click away** from falling into a political rabbit hole. Below, I've shown one of the many examples where a user was placed in a right wing rabbit hole from after only a single click, just by watching videos about Hurricane Milton.

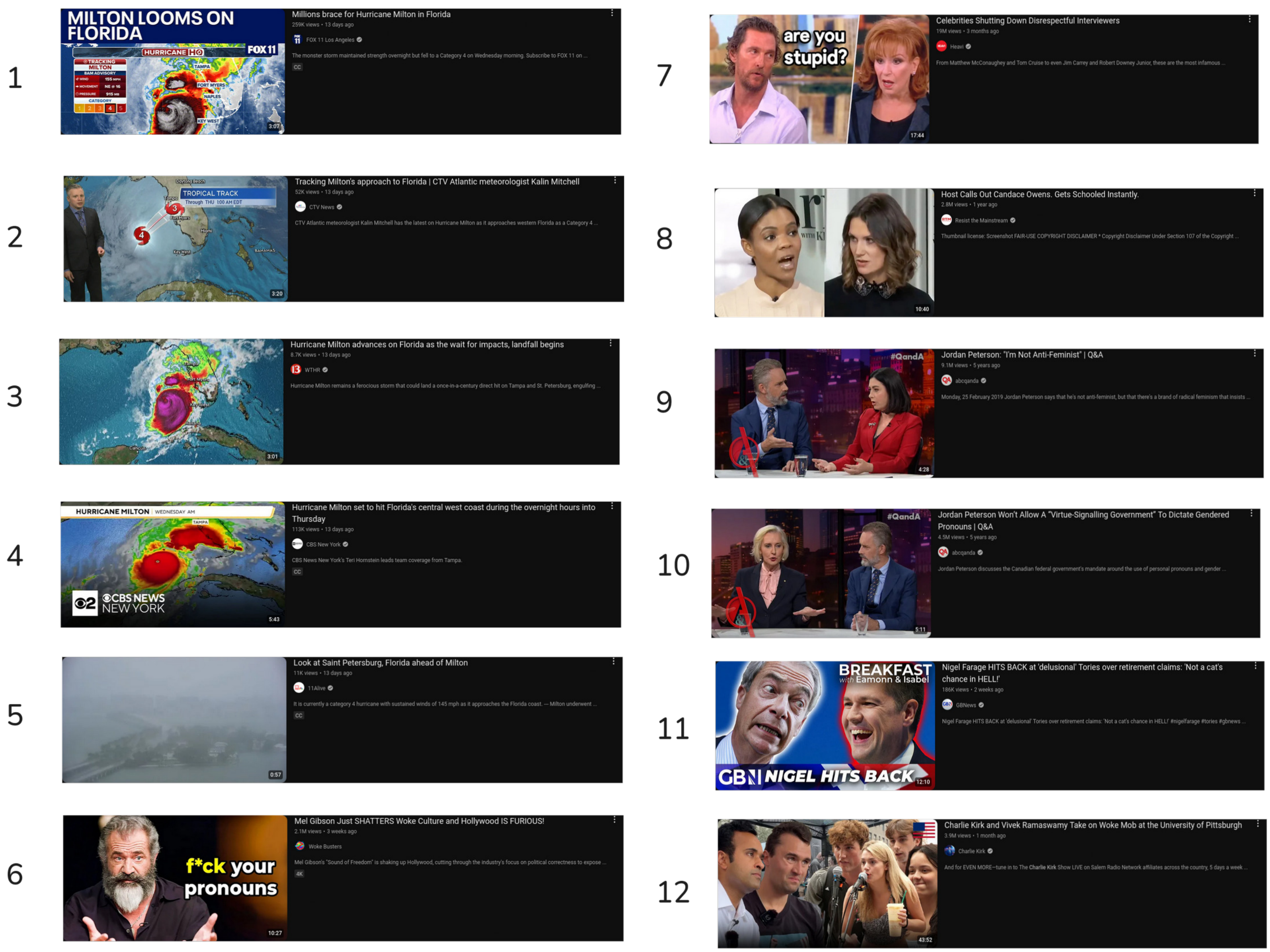



*Figure 8. User journey of bot #175. Note how the user was placed in the right-wing rabbit-hole after a single video click from a video about the leading news story of the day (Hurricane Milton).*

The result above is not an isolated incident, this also happened for bots #613, #737, #840, #879, #929, #971, and #973. And these are just the ones I found by skimming the results. I am sure there are still more cases like this in the dataset.

# Results – YouTube News Feed, independent media need not apply.

YouTube is a video content platform where anyone can create videos. For some reason, 96% (3/79) of the channels recommended in news feed section are entirely mainstream media (MSM) news. No other feed on YouTube has this kind of corporate MSM exclusivity.

The three non-MSM sources presented in my results are:

- Brian Taylor Cohen (YouTube's most successful anti-trump pundit that has spammed the platform for the past eight years with at least three "Trump Bad" videos a day)
- Johnny Harris (Independent journalist media with videos on international affairs and history)
- Our Changing Climate (Video essays on climate, justice, and socialism)

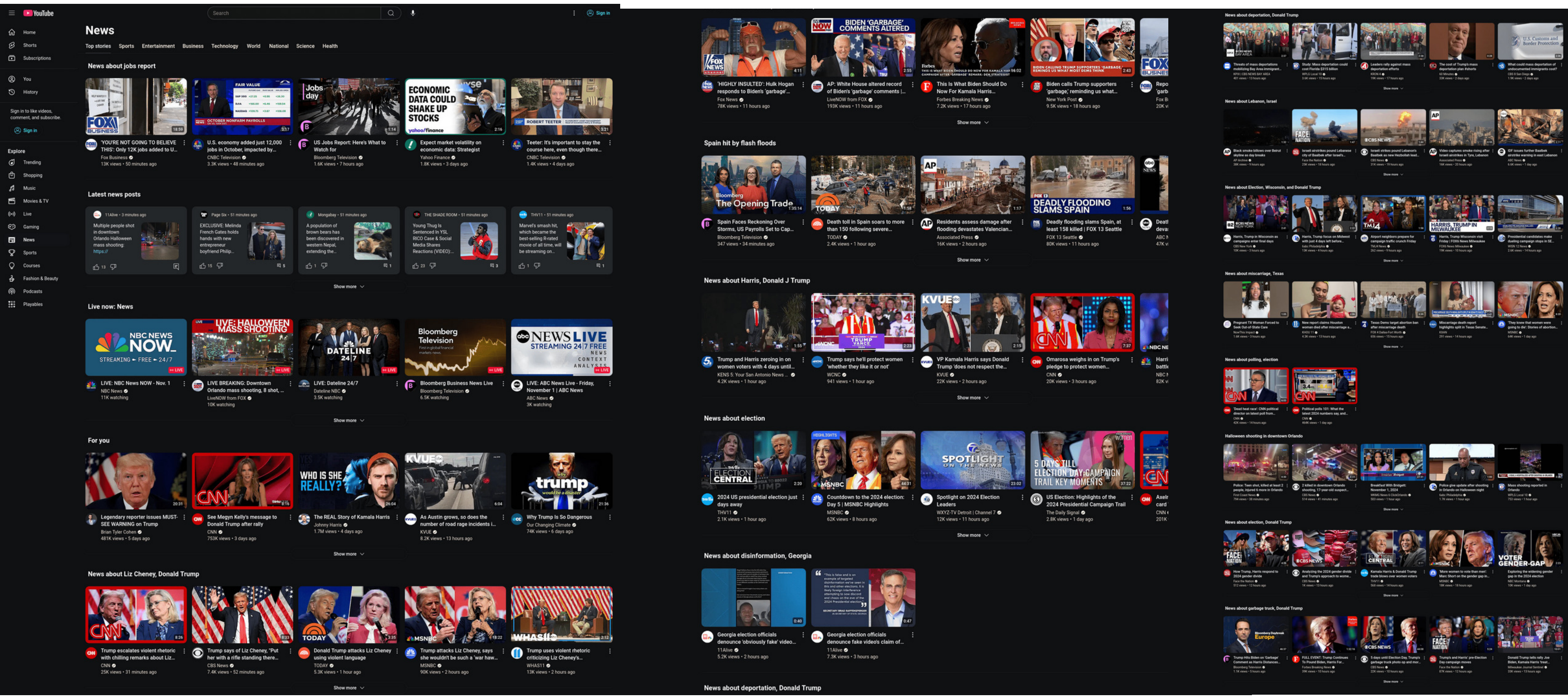



*Figure 9. YouTube News Feed*

# Results – Ideological networks

I define "ideological networks" as a network of entities that have similar ideologies. An example of this can be a collection of right wing media channels such as Fox News, Forbes Breaking News, and Sky News Australia channels.

In this section I will highlight four groups of ideological networks.

1. Mainstream media Democrat adjacent network
2. Mainstream media Republican adjacent network

3. Left wing influencer network
4. Right wing influencer network

In the recommendation networks below, the node size represents the number of recommendations for that video author, and the edge width represents the number of times one video author recommended another. Please note that node connections in a recommendation networks do not show ideological or content similarity, but simply which video channels recommend to other video channels.

> *Authors note: I would like to mention that there is no objective way to determine the boundaries between sub-networks. All networks are connected, however, certain nodes are connected to other nodes more frequently than others. I used the interactive version of the recommendation network and my own intuition and biases to determine the boundaries.*

## Mainstream media Democrat adjacent network

The Democrat adjacent ideological network is much larger than the Republican adjacent ideological network. The Democrat network has connections to various MSM news networks such as MSNBC, CNN, and CBS News. There are also connections to various late night and YouTube anti-Trump shows like Saturday Night Live, Stephen Colbert, Jimmy Kimmel Live, Seth Meyers, Brian Tyler Cohen and The David Pakman Show.

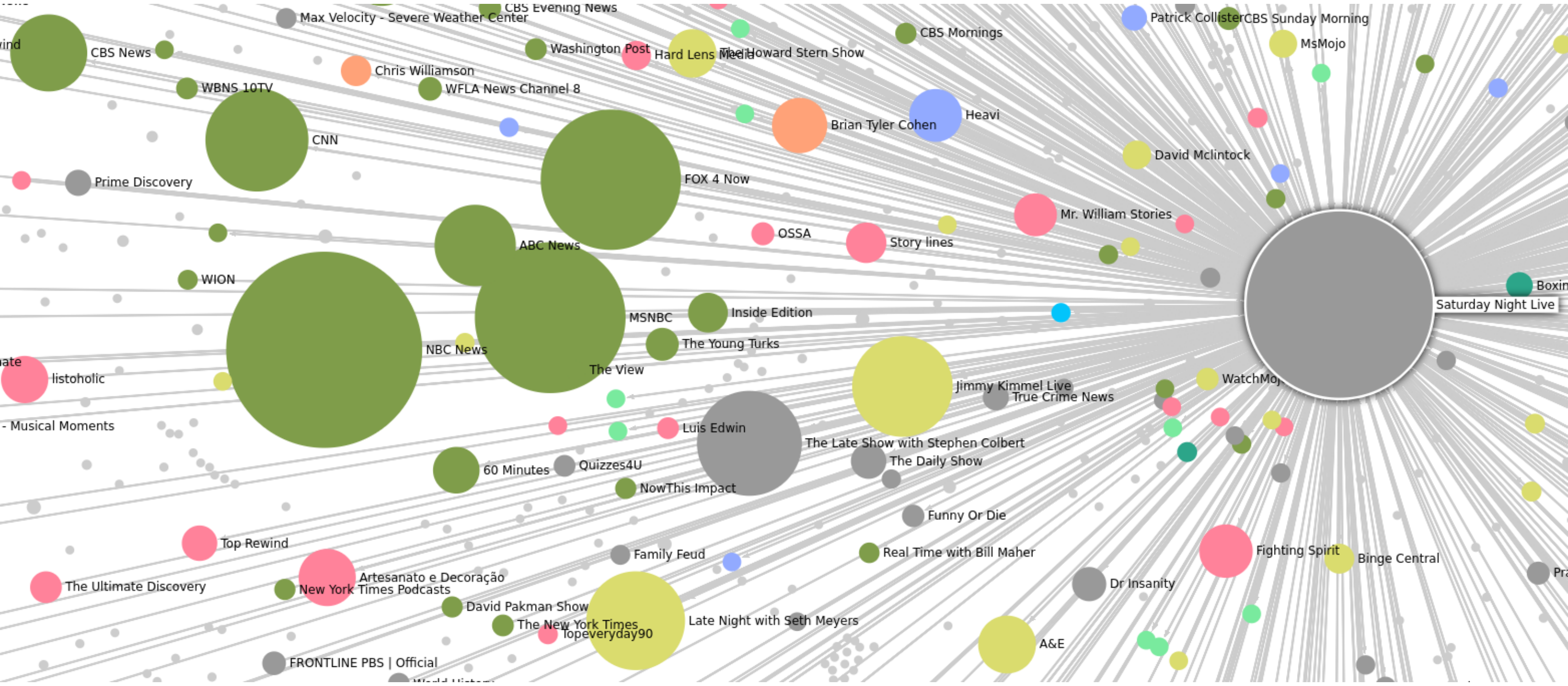



*Figure 10. An example of the mainstream media Democrat ideological network*

# Mainstream media Republican adjacent network

The Republican adjacent ideological network is a bit smaller and a lot more local than the Democrat adjacent ideological network. The Republican network has connections to various MSM news networks such as Fox News, Forbes Breaking News, and Sky News Australia. There are also connections to the majority of local American news.

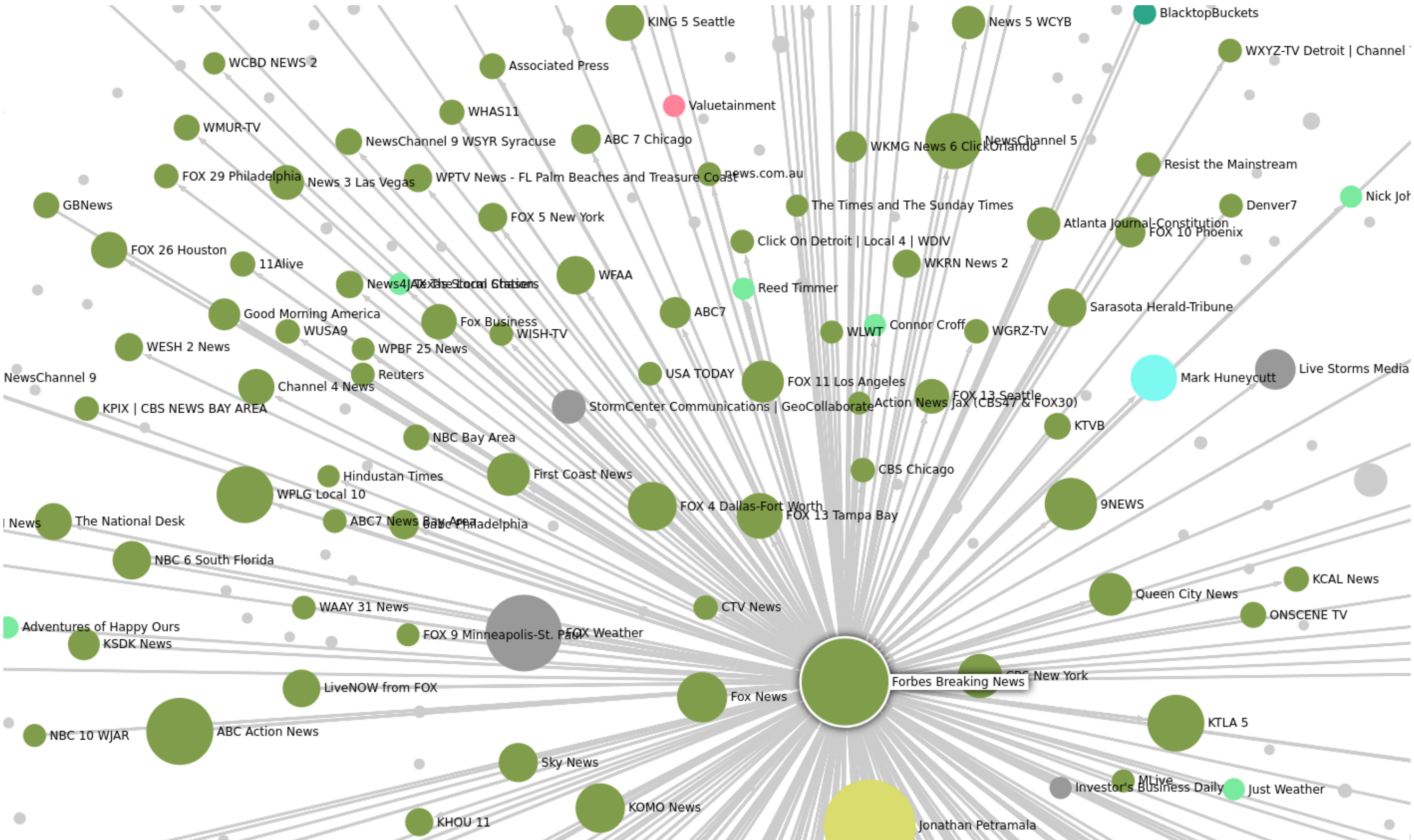



*Figure 11. An example of the mainstream media Republicans ideological network*

# Left wing influencer network

Recommendations for left-wing media and influencers are nearly nonexistent. I compiled a list of creators I found through my [research](). In total, only 1 video was recommended from this list out of the 520,000 recommendations

*Figure 12. Number of recommendation for various left wing content creators*

| Channel Name | Number of Recommendations |
|---|---|
| HasanAbi | 0 |
| F.D. Signifier | 0 |
| The Rational National | 0 |
| BenBurgisGTAA | 0 |
| BadFaithPodcast | 0 |
| Zoe Baker | 0 |
| Secular Talk | 0 |
| Second Thought | 0 |
| The Majority Report w/ Sam Seder | 1 |

*Authors note: The above list is not an exhaustive list of all left wing media creators, rather these are the ones the I am familiar with or have found during my research. I encourage the reader to download the recommendation data to see if they can find more. Also note, that I excluded certain YouTube channels that label themselves as progressive or left-wing, but are centrists, neoliberals, or whose content is primarily focused on anti-Trump videos.*

# Right wing influencer network

Have you recently noticed your YouTube homepage being flooded with right wing content such as "*Charlie Kirk and Vivek Ramaswamy Take on Woke Mob at the University of Pittsburgh*" and "*You Are NOT Oppressed Dave Rubin Calmly Destroys a Crazed Hyper Victim*"? It turns out that these videos are ideological entry points to more fringe right wing content, aka the "Alt-right Rabbit hole".

*Figure 13. Number of recommendation for various right wing content creators*

| **Channel Name** | **Number of Recommendations** |
|---|---|
| Rubin Report | 164 |
| Charlie Kirk | 103 |
| Jordan B Peterson | 29 |
| Douglas Murray | 16 |
| Timcast IRL | 7 |
| Ben Shapiro | 3 |

Compared with the right wing influencer network, the left wing one is virtually non-existent. Is the success of these channel organic or have these channels been propped up by various well-funded special interest groups?

According to my investigation, here is what I found about the financials of these creators:

- Rubin Report: A YouTube channel, that gets compensated for hundreds of thousands of dollars for each video posted by foreign entities such as Russia.
- Charlie Kirk: Runs a political non-profit organization called "Turning Point USA", that receives millions in funding.
- Jordan B Peterson: Former University of Toronto professor, turned right wing influencer. Estimated to have made more than $89M since his departure as a professor. Most of his net worth appears to come from touring.
- Douglas Murray: While their net worth isn't public, this influencer has extremely strong political connections. Specifically ties to foreign governments as Israel and having direct access to the world's richest man, Elon Musk.
- Timcast IRL: Another YouTube channel, that gets compensated for hundreds of thousands of dollars for each video posted by foreign entities such as Russia.
- Ben Shapiro: Co-founder of the Daily Wire. A media company with a annual run rate of $150M.

In the figure below, I showcase an example of a right wing ideological network from another experiment I collected.


*Figure 14. An example of a right wing ideological network*

From experience, right wing mainstream media news source like Forbes Breaking News or Sky News Australia, are usually followed by some popular right wing influencer like Jordan Peterson or Charlie Kirk, followed by more fringe racist and zionist, entities like Douglas Murray, The Free Press, and The Spectator.

Piecing together my personal user experience and observations from this study, ideological networks seem to contain three key node types.

- The first node represents ideologically aligned, socially acceptable to watch, mainstream media, for example "Fox News".
- The second node represents demographically adjacent, socially acceptable to watch, mainstream media, for example "The Joe Rogan Podcast" or "Oxford Union".
- The third node represents ideologically aligned, socially unacceptable to watch, non-mainstream, ideologically extreme media.

The existence of mainstream media is central to the introduction of less mainstream extremist media. Had mainstream entry-points not been provided, a user would have likely not found these kinds of videos and would have had to go out of their way to search for them. After all, this is what machine learning based recommendation engines excel at doing, discoverability and engagement.

# (Case Study) Real life applications of ideological networks: Hoover Institution & The Oxford Union.

One interesting application of ideological networks I found is that they can be used to uncover non-surface level ideological alignment. For example, prior to this study, I was aware of the existence of organizations like Hoover Institutions and Oxford Union after reading some of their material and watching some of their videos. I had unconsciously categorized them as conservative leaning, but primarily academic institutions.

However, after constructing the ideological network (figure from previous section), and subsequently doing more research on their content, I would probably tag them as neo-liberal & neo-conservative adjacent groups.

Let us dive deeper into some of their content.

## Hoover Institution, a public policy think tank at Stanford University.

This conservative institution is known for featuring some of the greatest thinkers of the 21st century such as:

- Dennis Prager, founder of the prestigious PragerU University. PragerU is currently approved to be used as education material across 7 US states and is growing year over year. PragerU will likely get accredited in Trump's presidency. America's education level is currently ranked 31 internationally.
- Douglas Murray, a dumb guy's smart guy, fascist mob promoter, and Netanyahu's mouthpiece,
- George Bush, former American president, Michelle Obama's cuddly friend, and the man behind the Afghanistan and the Iraq war that killed over 1,000,000 civilians and destroyed that part of the world for decades to come.

## Oxford Union, a debating society at Oxford University.

"*The Oxford Union is the world's most prestigious debating society with a tradition of hosting internationally prominent individuals*" according to the Oxford Union.

The debating society features prominent individuals and intellectual titans such as: Dennis Prager, Douglas Murray… and ~~George Bush~~, John Bolton …?

To a person reading about all this for the first time, it may seem odd why speakers with no academic merit, have long and well documented histories of promoting hate, or are responsible for the deaths of millions, keep getting invited to prestigious American and British universities. The answer is quite simple and it has to do with the title of this post.

Certain powerful individuals and organizations are trying to normalize certain ideologies for their personal benefit, whether it be economical (libertarianism) or political (neoconservatism, white nationalism, zionism). Unfortunately, American colleges seem to be their primary target.

*Authors note: To be fair, despite Oxford Union's political biases, it does feature speakers from the other side of the political spectrum, albeit to a lesser degree. This section is not aimed to be a jab at conservative or neo-liberal ideologies. This is more of a criticism of the low standards that Hoover Institution & Oxford Union set for themselves by inviting speakers who lack academic rigor and whose only claim to fame is being internet influencers, all while benefiting from the "Oxford" brand.*

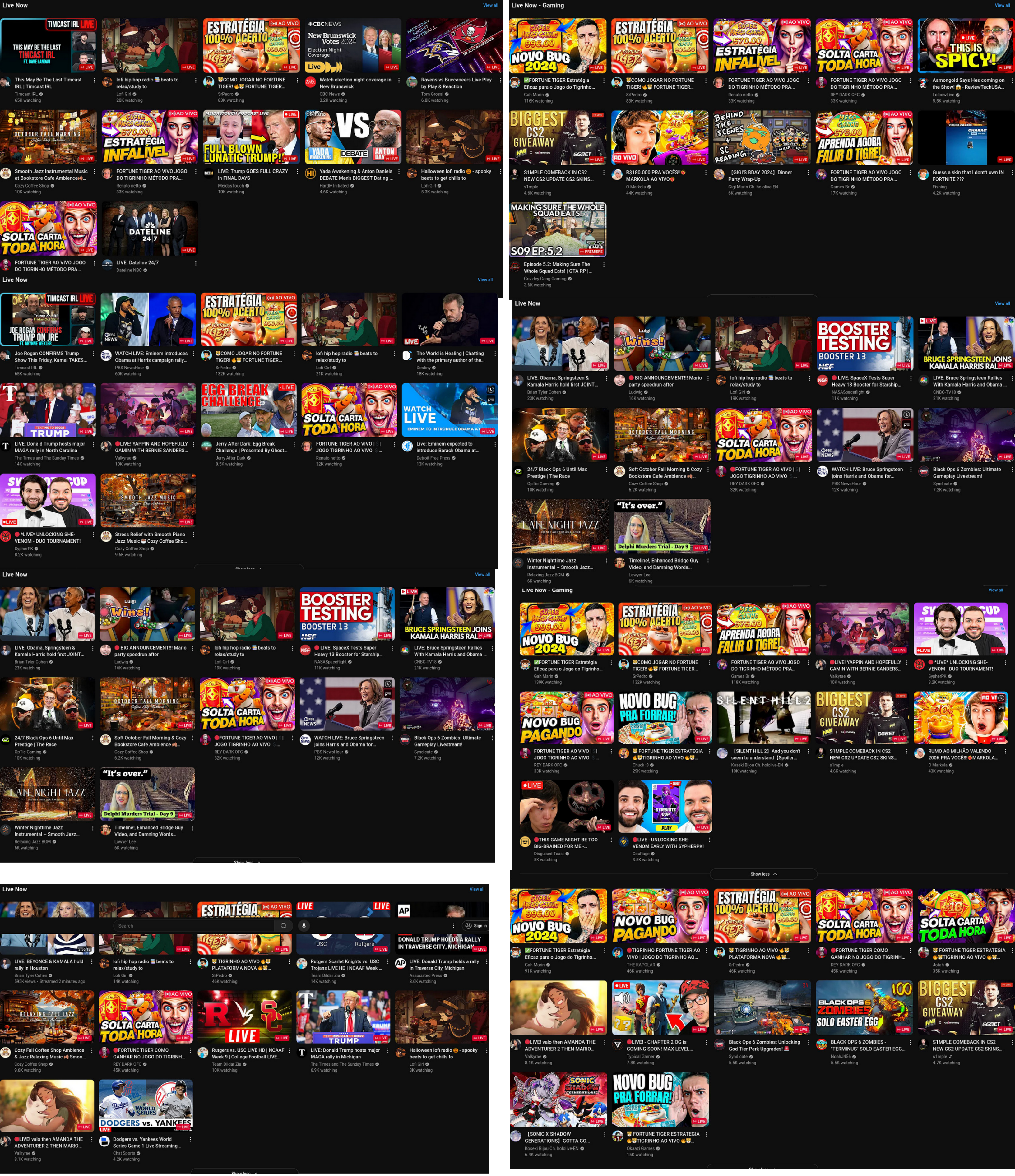
# Results – YouTube Live: Scraping the bottom of the barrel?

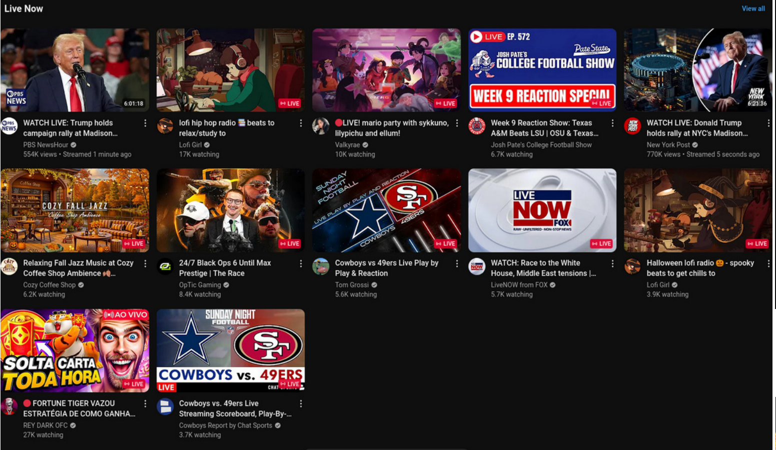
The live video genre or video streams is one of the most watched forms of video content. It is also one of the fastest growing content categories for children. The two biggest competitors in the video live streaming space are Twitch and YouTube, with Twitch being the more popular of the two. YouTube has has steadily been closing the viewership gap over the last couple of years.

What is responsible for YouTube Live's gain in popularity? Some hypothesize that YouTube's less strict community guidelines (with respect to Twitch) is the key reason, as several high profile Twitch streamers have migrated to YouTube Live after they were banned from the platform.

Fortunately for us, the YouTube Live feed recommends the highest viewed live streams so we can see exactly the kind of content that could be contributing to their increased viewership.

For my experiment, I have taken a screenshot of YouTube's top live and top live gaming channels once a day for 12 days at at around 00:00 UTC.


Live Now
Live Now - Gaming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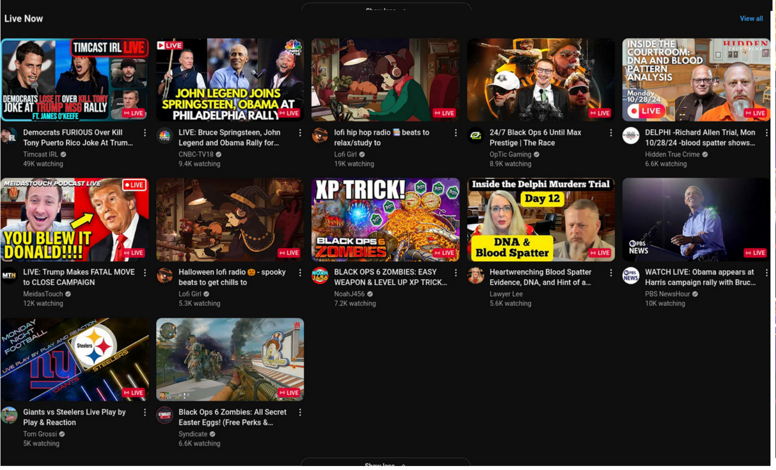
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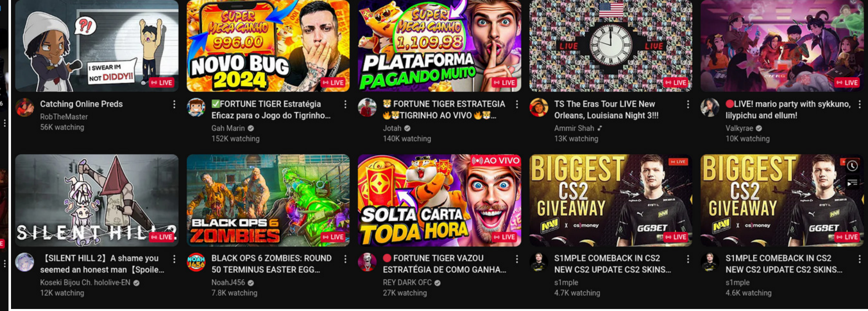

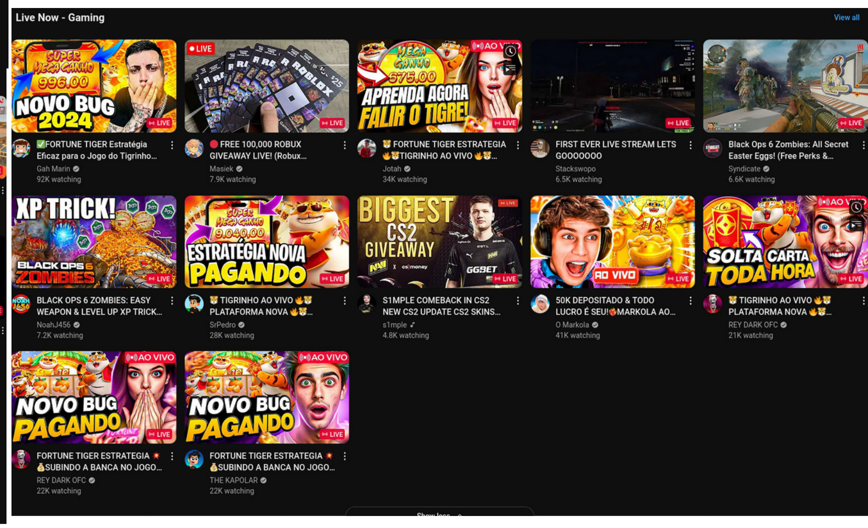
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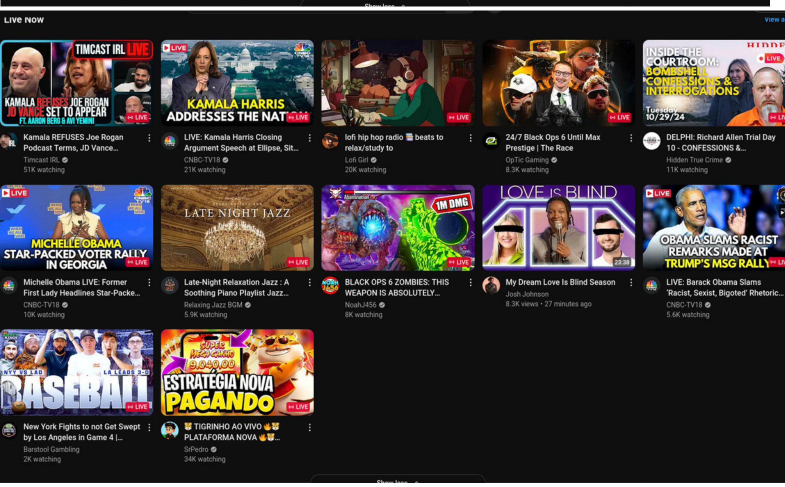
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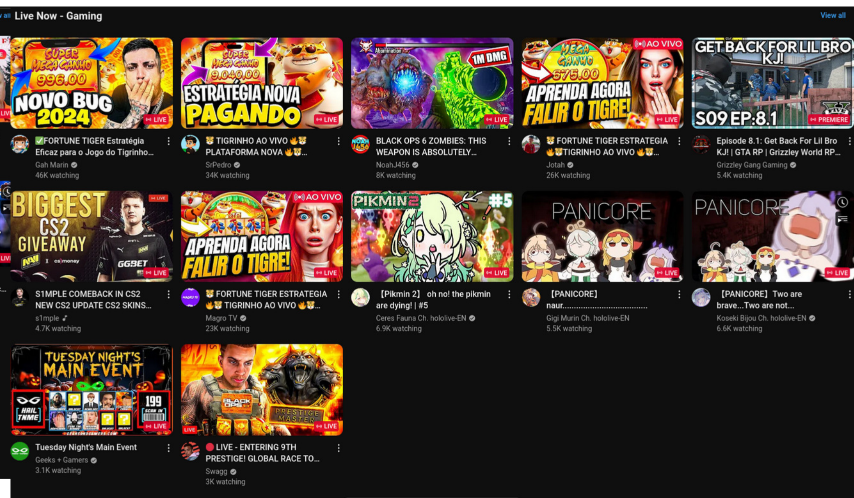
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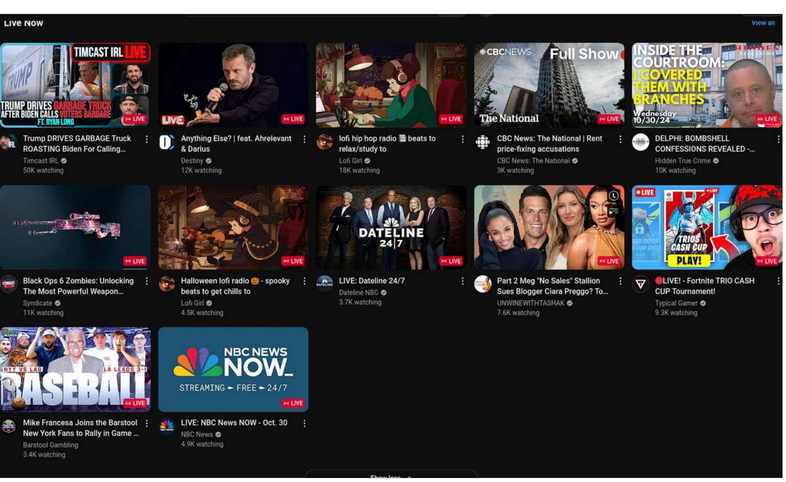
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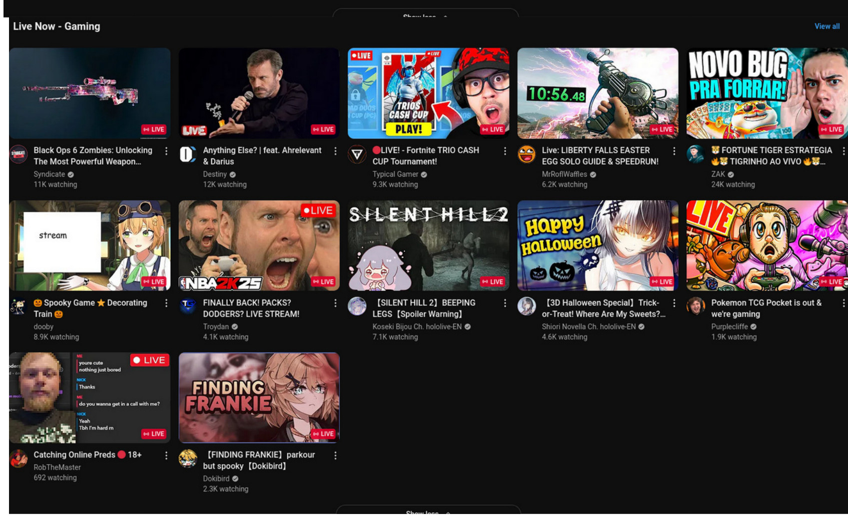
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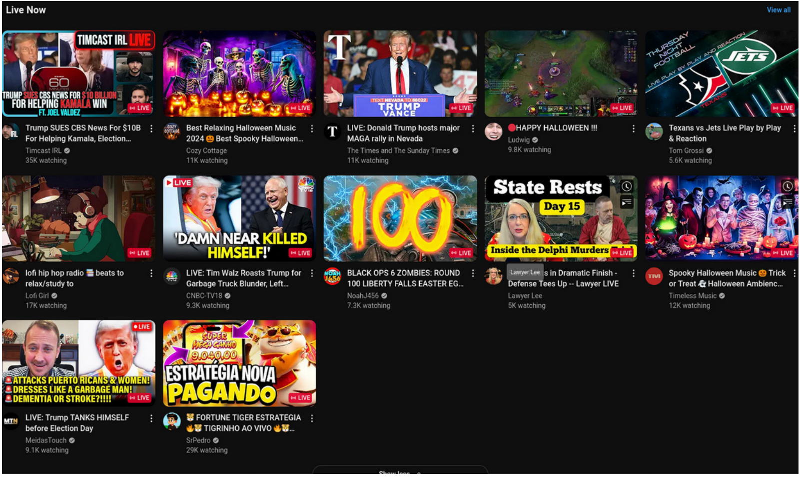
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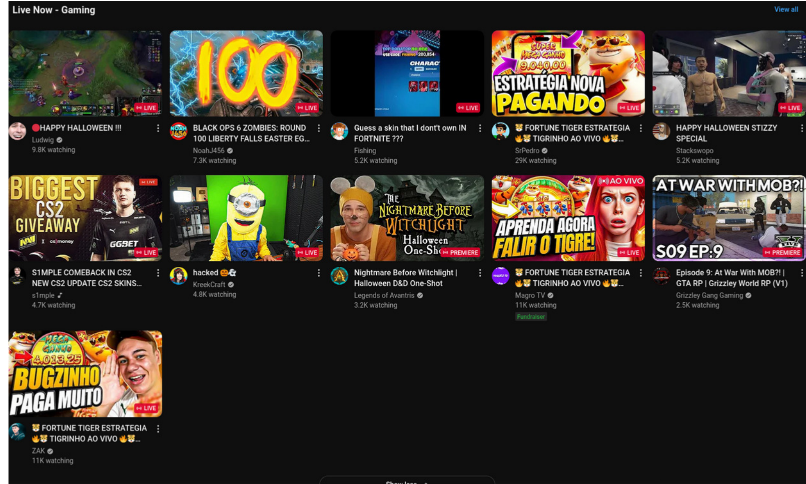
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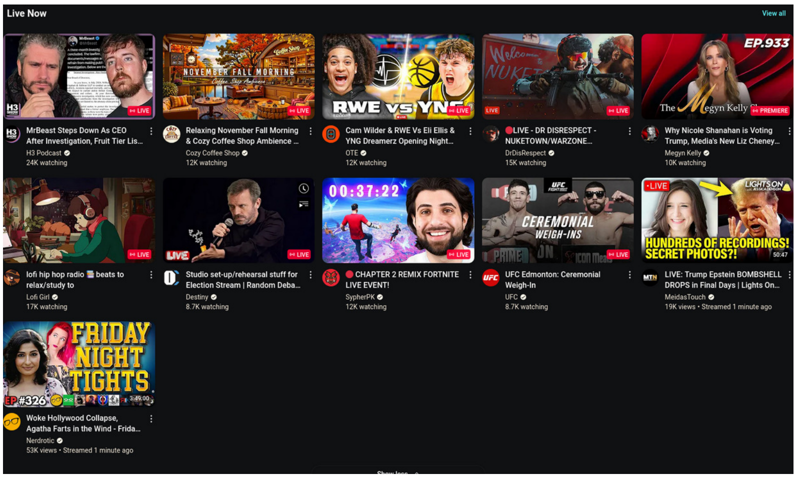
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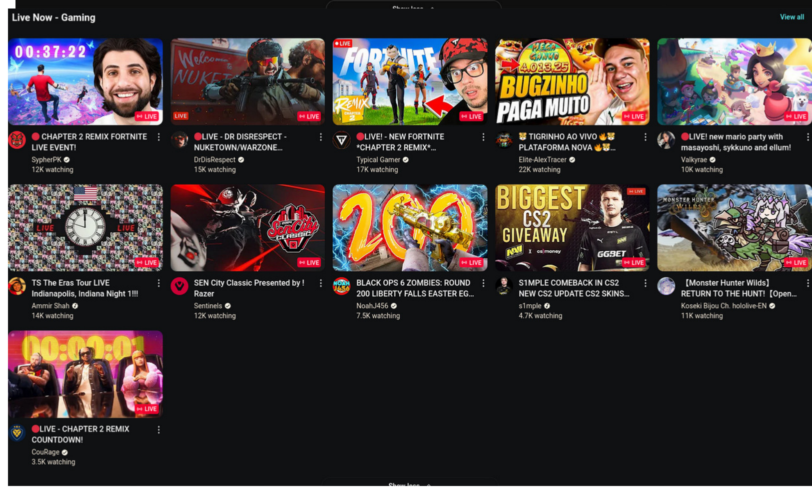
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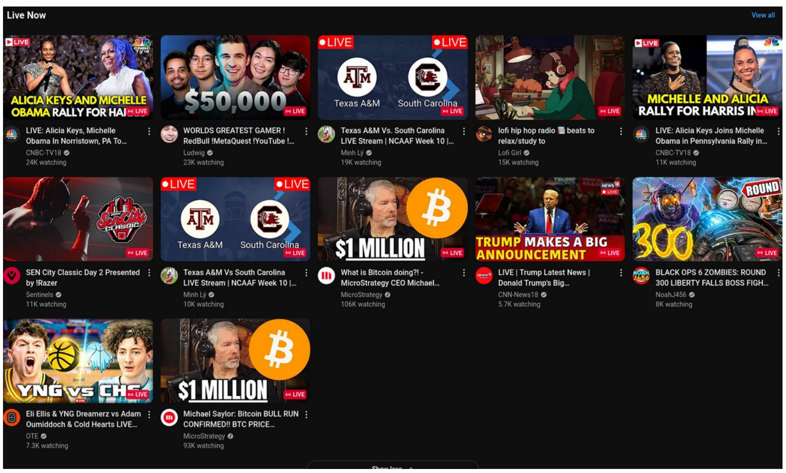
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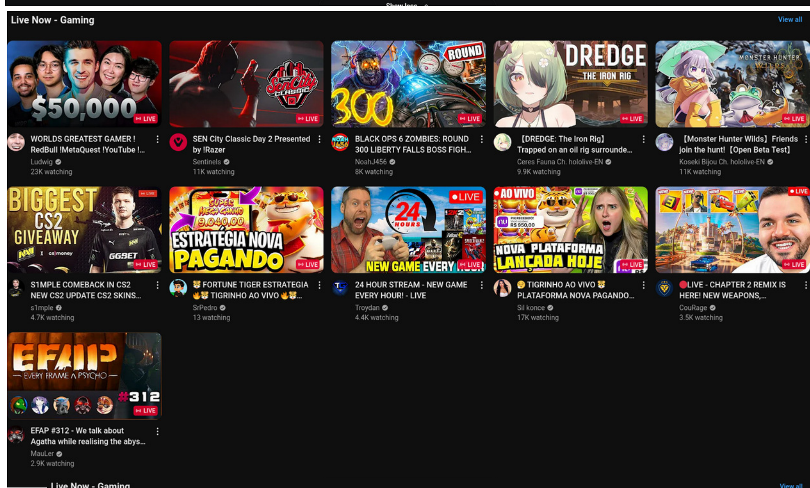
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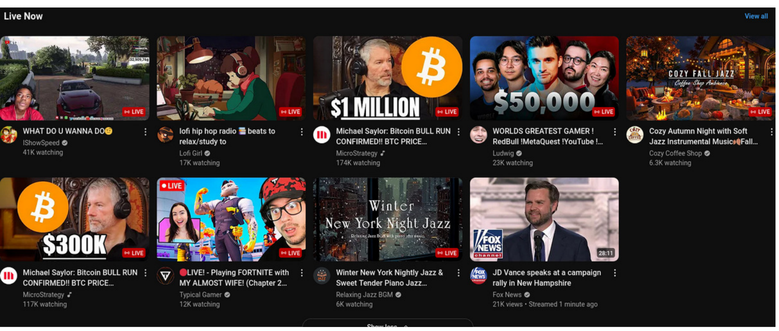
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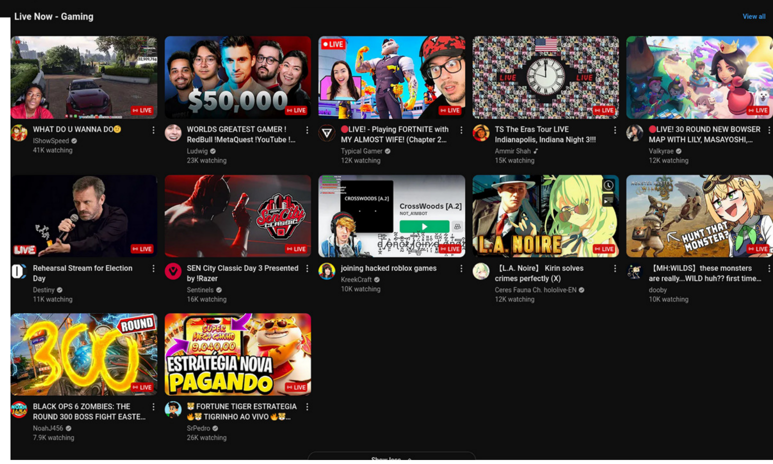
Live Now - Gaming
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*Figure 15. Daily screenshots of YouTube's live and live gaming feeds (screenshots at around 00:00 UTC everyday from 2024-10-21 to 2024-11-03)*

The following observations can be made:

- In the YouTube Live section
    - Gambling streams appear in 11/140 (8%) of the recommended videos, and appear at least once in 7/12 days (63%)
    - Crypto scam streams appear in 4/140 (3%) of the recommended videos, and appear at least once in 2/12 days (17%)
- In the YouTube Live Gaming section
    - Gambling streams appear in 41/140 (29%) of the recommended videos, and appear at least once in 12/12 days (100%)

Outside of gambling and crypto scam streams, the other recommended streams are not that much better. There are almost daily streams from culture wars streamers (Brian Taylor Cohen, MediasTouch, Nerdrotic) and bottom of the barrel political commentary streams (Timcast IRL, Destiny).

For those unfamiliar with the political streamers above, Timecast IRL, or Tim Pool is one of the largest pro-Republican political streamers. He is best known for inviting racists and sexists on his podcast as well as taking in hundreds of thousands of dollars from foreign governments for each video he posts.

Streamer Destiny is one of the largest liberal streamers. He is also known for inviting racists on his stream, getting banned from several streaming platforms for hate speech, and for expressing abhorrent opinions such as: Jim Crow not being racist, dropping a nuclear bomb on the Gaza strip would not constitute as genocide, and that Palestinians civilians are choosing to get killed by IDF soldiers in order to "farm Tiktok clicks".

The only normal streams, seem to be regular gaming streams, sports streams, news broadcasts, and music streams which comprise less than half of the recommendations. However, outside of specific gaming streamers, none of these seem to unique to the YouTube platform itself (music and news streams can be watched on many other platforms).

Given the choice to uphold YouTube's own community guidelines or selectively ignore it to make money, YouTube will likely chose the latter given the incentives are great enough. This is shown in YouTube's role in promoting streamers who participate in (a) culture wars, (b) gambling streams aimed children, (c) and political streamers with a history of promoting sexist and racist views.

# Discussion – Does YouTube have a political agenda?

**Question:** Is YouTube intentionally promoting right wing content because they have an agenda?

**Answer:** Likely not. Remember, YouTube/Google is a multinational corporation that is primarily driven by revenue and profit. Their agenda is not “far-right” or “woke”, their agenda is whatever makes them money (capitalism).

---

**Question:** Does that mean it’s more **profitable** to show polarizing right wing content?

**Answer:** Likely yes.

---

**Question:** But doesn’t this imply that YouTube is **intentionally** promoting right wing content to increase profits?

**Answer:** No.

---

**Question:** What about the leak from a Facebook whistleblower revealing that platforms like Facebook and Instagram **amplified angry and divisive content**?

**Answer:** The key to answering this question is to understand optimization objectives and human psychology. Both Facebook and YouTube use massive black box Neural Network Recommendation Systems (NNRS). NNRS are not built with an **explicit** objective on the kind of content it should show. NNRS **optimize for engagement**, and they are extremely good at doing so.

Both Google and Meta have thousands of engineers working on recommendation engines and spend billions of dollars each year between labor and compute CapEx. The type of technologies and innovations employed in their recommendation system divisions are sometimes years ahead of what academics are researching. The models used are trained on trillions of rows of user interaction data and are continuously improving day over day.

**It’s fair to say that the neural networks that power the recommendation systems of tech giants like YouTube and Meta are ugly and imperfect reflections of the collective unconscious of society.**

It’s ugly because it highlights how humans are drawn to negative, anger-inducing content, and it’s imperfect because, like any system, YouTube can be exploited by billionaires who spend millions to normalize harmful narratives and manufacture consent.

There are several studies that show negativity and anger are the most influential emotions in increasing online engagement. Therefore, if NNRS are in fact efficient models of human behavior and are trained with the goal of increasing engagement, these models will likely recommend divisive content.

*Authors note: Beware of certain kind of "whistleblowers" or individuals who warn about the dangers of a specific technology without a deep understanding of the how the tech works. This is especially true if they happen to be secretly backed by the CIA or are former CIA agents themselves. There is almost always an ulterior motive for them calling for an increase in "content moderation". There will be a future post on this topic.*

# Putting it all together – How YouTube is used to "Manufacture Consent"

"Manufacturing consent" is a term coined by American economist Edward S. Herman and American professor Noam Chomsky in their book "Manufacturing Consent: The Political Economy of the Mass Media". In their book, they argue that the mass communication media of the U.S.:

> "A*re effective and powerful ideological institutions that carry out a system-supportive propaganda function, by reliance on market forces, internalized assumptions, and self-censorship, and without overt coercion*".

Herman and Chomsky propose that mass communication media distort information through five key filters. In the following, I will outline each of these filters and examine how they apply to YouTube.

1. **Size, Ownership, and Profit Orientation:**
    - Description: Mass-media corporations require significant capital to start up, scale, and gain substantial market share. Consequently, almost all decisions made by these corporations must cater to their owners, shareholders, and investors.
    - YouTube: Promoting engaging content by any means necessary is crucial for increasing total watch time and ad revenue. As a result, YouTube often promotes culture war and right-wing rage-bait content, which tends to draw in the large and engaged audiences.
2. **Advertising License to Do Business:**
    - Description: Similar to the first point, the primary recurring revenue source for these corporations is advertisement. Therefore, these corporations must prioritize monetary interests to cater to advertisers.
    - YouTube: In the first section of the post, we explored how YouTube recommends mainstream media channels over smaller independent creators, despite independent YouTubers having higher channel engagement rates as measured by the self-recommendation rate. Additionally, mainstream media benefits from being more advertiser-friendly and having brand recognition, making them YouTube's go-to recommendations.
3. **Sourcing Mass Media News:**
    - Description: Powerful organizations subsidize mass media, granting them privileged access to news, while alternative sources struggle for attention, leading to editorial biases that favor established interests.

    - YouTube: As observed on the YouTube News feed, 97% of news shown comes from large mainstream media outlets. To reach the largest audience possible, news sources must be posted on social media platforms like YouTube. Unfortunately, this undermines smaller independent media, as big tech platforms like YouTube siphon off their revenue.
4. **Flak and the Enforcers:**
    - Description: Flak refers to negative backlash against specific types of media content, often resulting in financial consequences such as loss of ad revenue for mass media corporations. Flak can be wielded as an enforcement tool by powerful and influential individuals or organizations.
    - YouTube: While not explored in this study, YouTube has a history of demonetizing channels that hold opposing ideological views outside the socially acceptable Overton window. There are even instances where creators make videos condemning social injustices only to have themselves demonetization or punished for breaking YouTube's community guidelines, while the actual perpetrators of the injustices are left untouched. Since these topics cannot be engaged in an advertiser friendly way, content creators have less incentive to cover them.
5. **Anti-Communism:**
    - Description: Generally refers to any group considered a "common enemy." In the United States during the Cold War, anti-communism served as a tool for those in power to suppress dissent. In more recent times, this role has shifted to the "war on terror" as a means of social control.
    - YouTube: Similar to previous section.

# Closing Remarks

In my analysis, I explore how mainstream media often serves as an entry point for more radical right wing content. Without mainstream media, this far right views would likely remain obscure. On the other hand, left wing content faces a significant hurdle: a financial one. This is tied to the left wing ethos; if you believe billionaires shouldn't exist, why would a billionaire fund your cause? The only option left-wing creators have to make large amounts of money is either to become right-wing grifters (as discussed in the next paragraph), or to cave in to the Democratic Party. There is a reason why the most successful "progressive" YouTubers are almost all anti-Trump spam posters.

The amount of money flowing to right wing social media Republican billionaires is staggering. In my personal opinion, this is likely the reason why so many liberal or centrist political iufluencers such as Jordan Peterson, Dave Rubin, Candace Ownes, Russel Brand, and others like them have turned away from their initial beliefs to join the far-right echo chamber. This is further supported by the fact that we rarely see right wing individuals joining progressive movements, as the core values of the two movements are fundamentally incompatible.

The concept of the "Overton window", a theory coined by political analyst Joseph Overton, which describes the range of ideas considered acceptable in public discourse. The large amounts of money being channelled into right wing social media is done with the purpose of making previously fringe ideas, mainstream.

Could the change of the Overton window on YouTube and other social media have been an important influencing factor of the unprecedented results of the 2024 US election? Data collected by from the peak viewers channel on Twitch Tracker, shows that in the 2024 US elections, 9 of the 10 most viewed streams during the 2024 American elections were all from right wing creators. Of these 9 creators, 7 initially built their audiences on YouTube or used it as their primary platform.

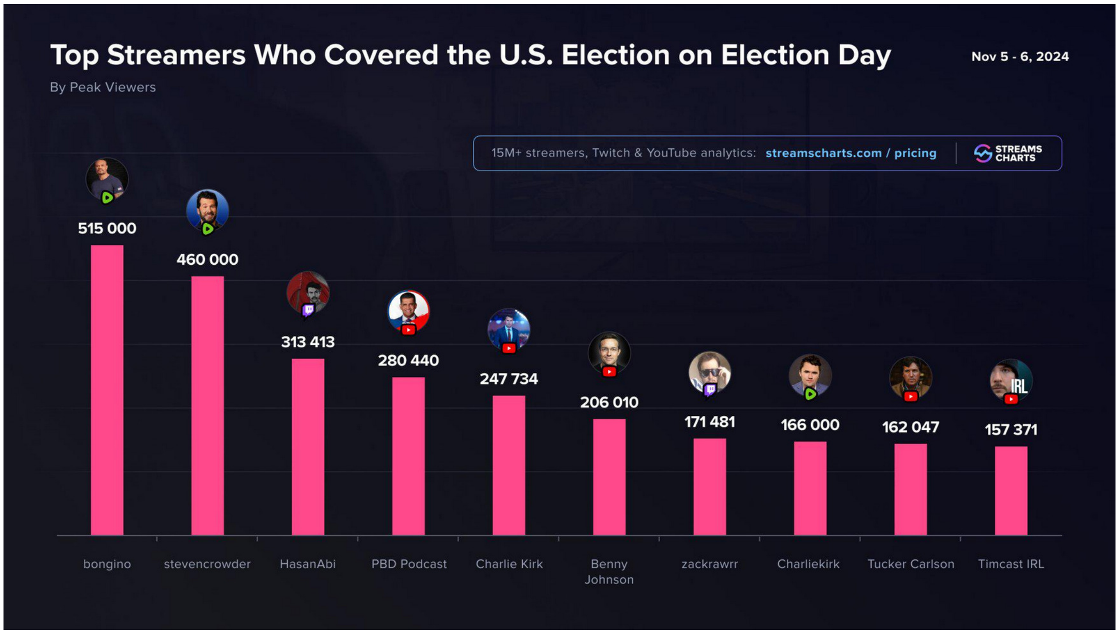


*Figure 16. Most viewed streams during the 2024 American elections. Data from Twitch Tracker.*

"Growth at All Costs" seems to be the game that Google is playing. As long as YouTube and YouTube Live continue growing, making money, and taking market share away from competitors like Twitch, they will continue lowering the bar in terms of their community guidelines, platform integrity, and content quality.

The changing Overton window on YouTube parallels the company's internal culture. When Google was first founded, their unofficial motto was "Don't be evil", only to be later changed to "Do the right thing". In reality, their motto should be, "Don't be evil, unless its profitable".

As we conclude this story, it's important to note a relevant finding from a Pew Research Center survey. The survey revealed differences in perceptions of social media censorship between Republicans and Democrats:

90% of Republicans believe their views are censored on social media platforms.

59% of Democrats share this sentiment.

This perspective is frequently expressed by conservatives and former President Donald Trump. However, the results of this study shows the opposite: republican, democrat, and far-right views are promoted more than independent progressive voices on YouTube.

Given this information, we might wonder why former President Donald Trump was systemically banned on almost all mainstream social media platforms in 2021. Was this truly due bias against conservatives? Was it due to incitement of violence on January 6? Were there other reasons? One lesser known explanation for this will be explored in a future investigation.

# Methods

## Requirements

The goal of this experiment is to understand how the YouTube Algorithm influences the type of content people consume. To accomplish this, I would need to create a bot that is capable of scraping YouTube. However, there are several challenges that arise due to the sheer scale of the YouTube platform. Some of the challenges include YouTube's vast content library of over 10 million videos, constant retraining of recommendation models every minute, and the execution of dozens of concurrent A/B tests. Taking all these challenges to account, the bot should be built with the following requirements:

- Unbiased – Reduce human bias with respect to video selection & influence from external factors such as updates on YouTube.
- Scalable – The bot should scale to generate hundreds of thousands of datapoints, in order to explore a representative sample of the YouTube content library.
- Flexible – Since the runtime config of the bot will influence the results, having tune-able parameters will allow me to test different hypothesis.

## The Bot

The bot made for this investigation is no different than any other web scraping bot. I won't get into the details of the software to avoid getting method potentially blocked. I would like to be able to run similar experiments in the future.

## Experiment Setup

### Runtime loop

As mentioned in the earlier sections, YouTube uses a different serving model for each type of feed. During testing, I noticed that depending on which feed I use, I would get drastically different results. The video feed (where recommendations are on the right side of whatever you are watching), tend to be heavily influenced by what the user is currently watching. During testing, I noticed that if the bot just uses the video feed, it would get stuck watching the same kind of video over and over again. For example, if the first video watched happens to be a Fortnight video, the next 100 videos are likely to be Fortnight videos.

In contrast, the home feed (the videos you are recommended on the home page) tends to be more diverse as they are influenced by current trending videos in the user's geography as well as the user's watch history. During testing, I noticed that if the bot just uses the home feed, the bot would only visit surface-level mainstream content categories (e.g. news, entertainment, music videos, gaming).

Taking these observations into account, the bot I developed alternates between watching N videos from the video feed and then switching to the home feed to watch a video there. Testing has shown that this approach maximizes the discoverability of non-mainstream content.

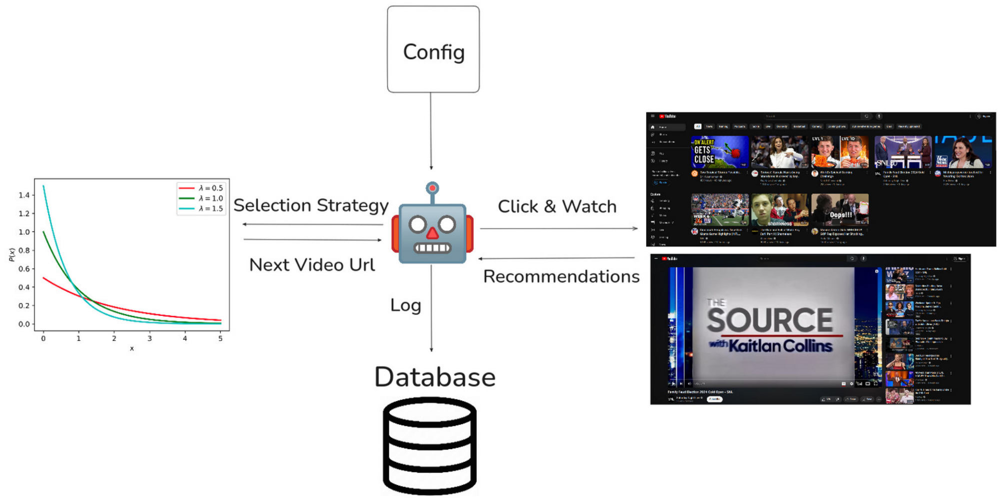


*Figure 17. The YouTube bot runtime loop.*

## Bot Actions

Like all advanced recommendation systems, YouTube's recommendation system is a feedback loop that is influenced by the user's actions. The two main actions are:

- "Click", where a user clicks on a recommended video
- "Watch", where a user watches a video for N amount of seconds.

Of course there are thousands of signals that YouTube logs such as whether someone subscribers, how much of the video they watched, whether they skipped large sections of the video, etc... However, in terms of optimization objectives, click and watch are the most important.

With the goal of being as unbiased as possible, I decided that the bot randomly selects a video from any feed, and watches a video for any time between 30 seconds to 3 minutes.

Since the bot was created with flexibility in mind, hyperparameter can easily tuned to modify the bots behavior. Below is a list of hyperparameters used by the bot cluster.

- Number of concurrent bots
- Watch time (seconds)
- Total number of videos to watch
- Runtime loop journey (e.g. how many videos to watch in home, video, shorts, news feeds)
- Video click selection strategy (e.g. given a list of recommended videos, which one should the bot watch next)
- Geolocation (specifies which server the bots run in; this is helpful to study how the recommendation differs between countries)

## Video click selection strategy

The YouTube algorithm behaves differently depending on the user's behavior on the platform. Therefore, how the bot interacts with the site will directly effect the results of the experiment. Should the bot model real user behavior or should it choose videos randomly to be as unbiased as possible?

Both scenarios would be useful to measure. Therefore, I created several video click selection strategies to model different types of behavior.

### Random Uniform Selection

Given a list of recommended videos, this selections strategy samples a number from the random distribution. In other words, all videos are considered equally and the video is chosen at random.

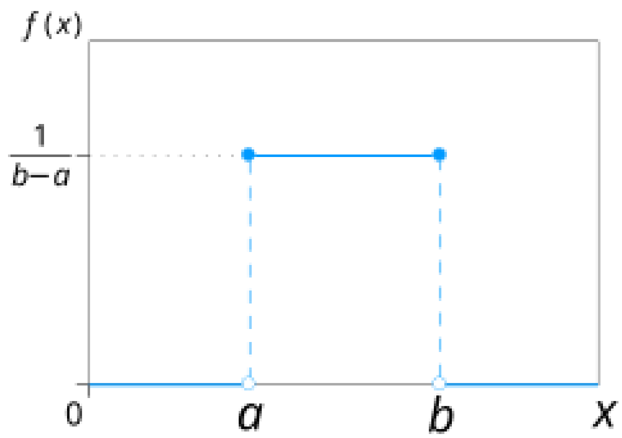


*Figure 18. Continuous random uniform distribution.*

The advantage of this method is that it's the most unbiased way of selecting videos. Unfortunately, YouTube's recommendations are ordered by relevance. Meaning the higher the video is on the feed, the higher that YouTube internally ranks that video. In the video feed, YouTube displays around 20 recommendations, while the home page can show over 30. However, less than 30% of these are visible on the user's current screen, as they would need to scroll down to view the rest.

**Random Exponential Selection**

Given a list of recommended videos, this selections strategy samples a number from the exponential random distribution. In other words, the higher the video is on the recommendation list, the higher the chance of selecting it.

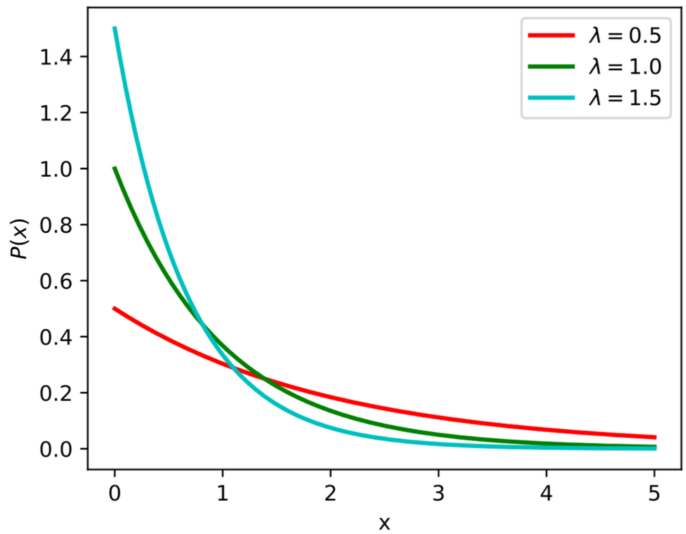


*Figure 19 Exponential random uniform distribution.*

The advantage of this method is that the probability of selection is aligned in terms of distribution of the relevance scores of the YouTube recommendation model. Furthermore, recommendations that are currently visible on the user's screen will naturally have a higher chance of being selected. Unfortunately, methods that select videos randomly or based on ranking position in the feed, don't necessarily capture the complexity of human behavior.

However, since 1000 bots will be watching over 20,000 videos, using a random exponential selection strategy could provide a generalized view of how YouTube's video recommendation system works. For the experiment shared above, an exponential distribution with a $\lambda$ of 0.25 is used as the selection strategy.

**Persona/LLM based selection**

To simulate how a real user would behave, this selection strategy uses a [large language model] (LLM) to model a user specified persona. For example, you could prompt the LLM to give probabilities of watching a video given it's title and given a user persona.

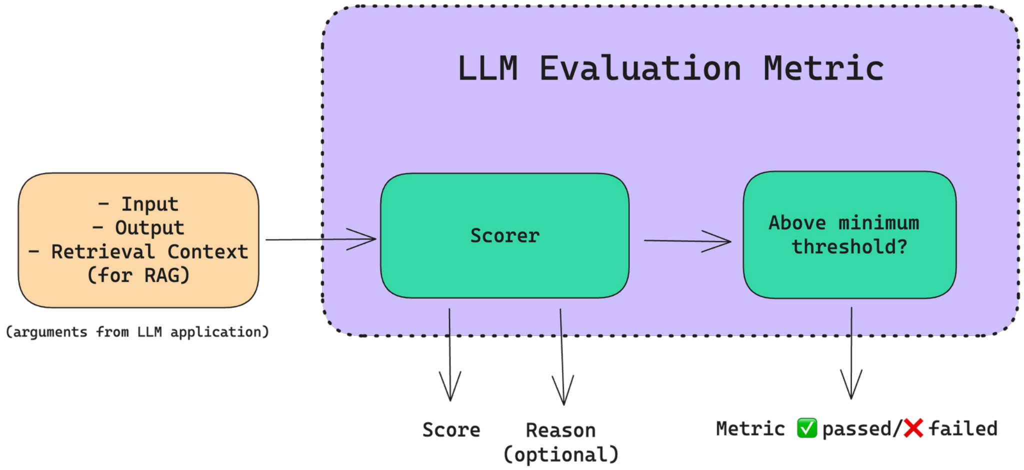


*Figure 20. LLM based ranking system.*

In my opinion, this method is the most accurate way to do behavior modelling at scale. At Google and other big tech companies, LLMs are used in their model optimization process in order to evaluate the relevancy of recommendations returned from their ranking models.

While this methodology is the most realistic, it does have several drawbacks, with the main one being that its resource intensive. An additional limitation is that real user would also be influenced by the video's thumbnail as well as it's rank in the recommendation feed. While [multimodal LLMs] exist, lots of time would need to be spent on fine-tuning a set of hyperparameters that would give realistic results.

**Scalability**

To ensure scalability, the bot had to be as lightweight and parallelizable as possible. During stress testing, I was able to scale out to 50 concurrent YouTube bots per machine. For my setup, scaling was bound by the network bandwidth. The actual number used during experimentation is less than half of that, as the point of this experiment isn't to make YouTube pay high egress fees or mess with their advertiser analytics. Also the higher the number of bots used the higher the chance of potentially getting IP banned.

Scalability is extremely important in this experiment because of time effects. Running the experiment in the shortest amount of time possible limits the influence of things like breaking news, viral videos, and changing trends. From the platform side, YouTube is continuously training their recommendation model every couple of minutes and running dozens of A/B tests behind the scenes. Fast experiment times and high concurrency limit external factors and insures all bots are starting from the same place.

# Data Availability

## Bot Data

All bot experiments referenced in this document can be downloaded from here.

There are three experiments used:

bot_news, a supplementary experiment with a news feed focused runtime. Created from 100 bots.

bot_big, the main experiment used with over 500,000+ recommendations.  Created from 1000 bots.

bot_small, an alternate experiment based in the UK. Created from 100 bots.

When "selected_item_idx" == "key", these are videos the bot watched, else they are recommendations.

## Recommendation Network

A 17MB black and white recommendation network can be downloaded from here.

A 52MB colored recommendation network can be downloaded from here.